Assimilation of All-sky Microwave and Infrared Brightness Temperatures for Hurricane Prediction

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Introduction

EnKF assimilation of all-sky IR observations of hurricanes makes great intensity and track forecasts (e.g., Zhang et al. 2019 BAMS)

Can assimilating microwave observations improve precipitation forecast/analysis?

- Forward model: Community Radiative Transfer Model with custom microwave cloud scattering properties (Sieron et al. 2017, 2018)
  - Consistent with WRF microphysics PSDs
  - Substituting spheres with non-spherical particles (Liu 2008, MWR)

Using sector snowflakes for snow species drop BTs at 183.31 GHz in-line with observations (Figures 1 and 2).

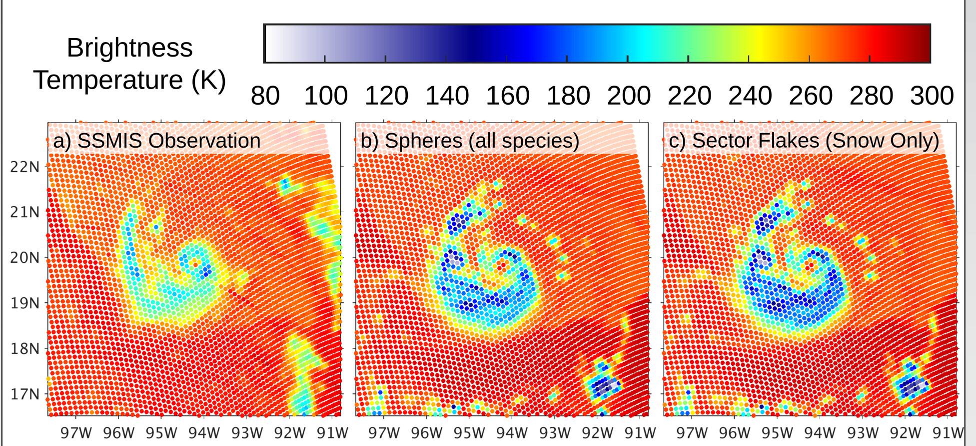

Figure 1. (a) F16 SSMIS observed brightness temperatures (K) at 91.7 GHz (SSMIS channel 18). CRTM-simulated 91.7-GHz brightness temperatures using (b) cloud scattering properties based on microphysics-consistent spheres for all ice species and (c) sector snowflakes in place of the spheres for the snow species.

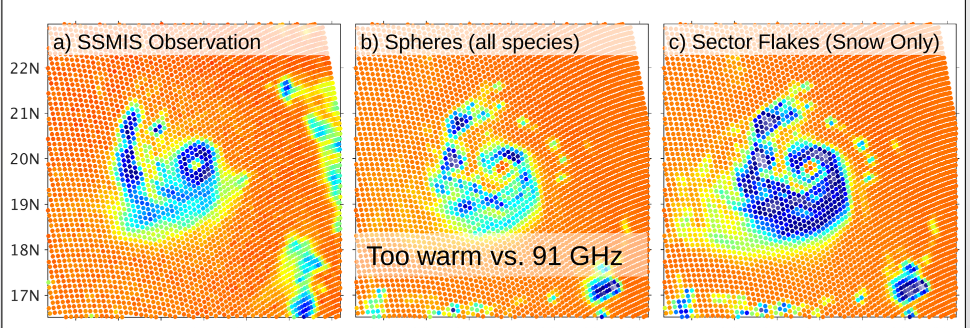

Figure 2. Same as Figure 1 but for 183.31 GHz (SSMIS channel 9).

Application to Harvey

Case: Harvey (2017) while in the Gulf of Mexico
- Ensemble spin-up from 23 Aug. 00-12 UTC
- 13 cycles from 23 Aug. 12 UTC to 24 Aug. 00 UTC
- PSU-EnKF system (citation), hourly cycling
- Assimilation only in the inner domain, but replacing the environment with GFS every 6 hours

Observations: conventional, ABI channel 8 (*upper-level water vapor*), 19 GHz V-pol (19V) and 183.31±7 GHz

Experiments:
- All experiments assimilate conventional observations and hurricane position and intensity (HPI)

1. Only conventional: *NOSAT*
- All other experiments assimilate infrared observations at hours with no microwave observations

2. Just IR at every cycle (*IR*)
3. 19V and 183±7 (no IR) when available (*MW*)
4. *MW* but excluding over-land MW and clear-sky 19 GHz observations (*MW_lmt19*)
5. *MW_lmt19* but IR at all cycles (*IR+MW_lmt19*)

Tools
- An interpretation on successive covariance localization (Zhang et al. 2009, MWR)
- Relaxation to prior perturbations (RTPP; Zhang et al. 2004, MWR): 0.75
- Adaptive Observation Error Inflation (AOEI; Minamide and Zhang 2017, MWR)
- Adaptive Background Error Inflation (ABEI; Minamide and Zhang 2019, QJMRS)

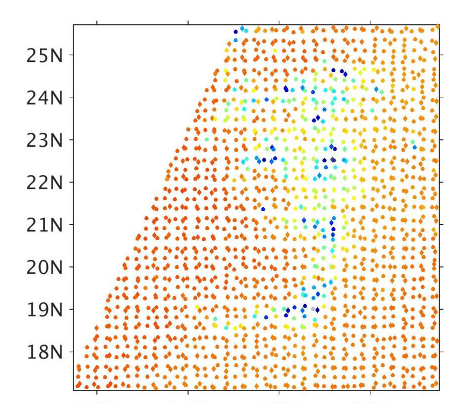

Figure 3. Diamonds and circles show 183±7 observations assimilated with a 200-km and 60-km ROI, respectively, filtered from the 23 Sept. 12 UTC GMI full observation swath.

Results

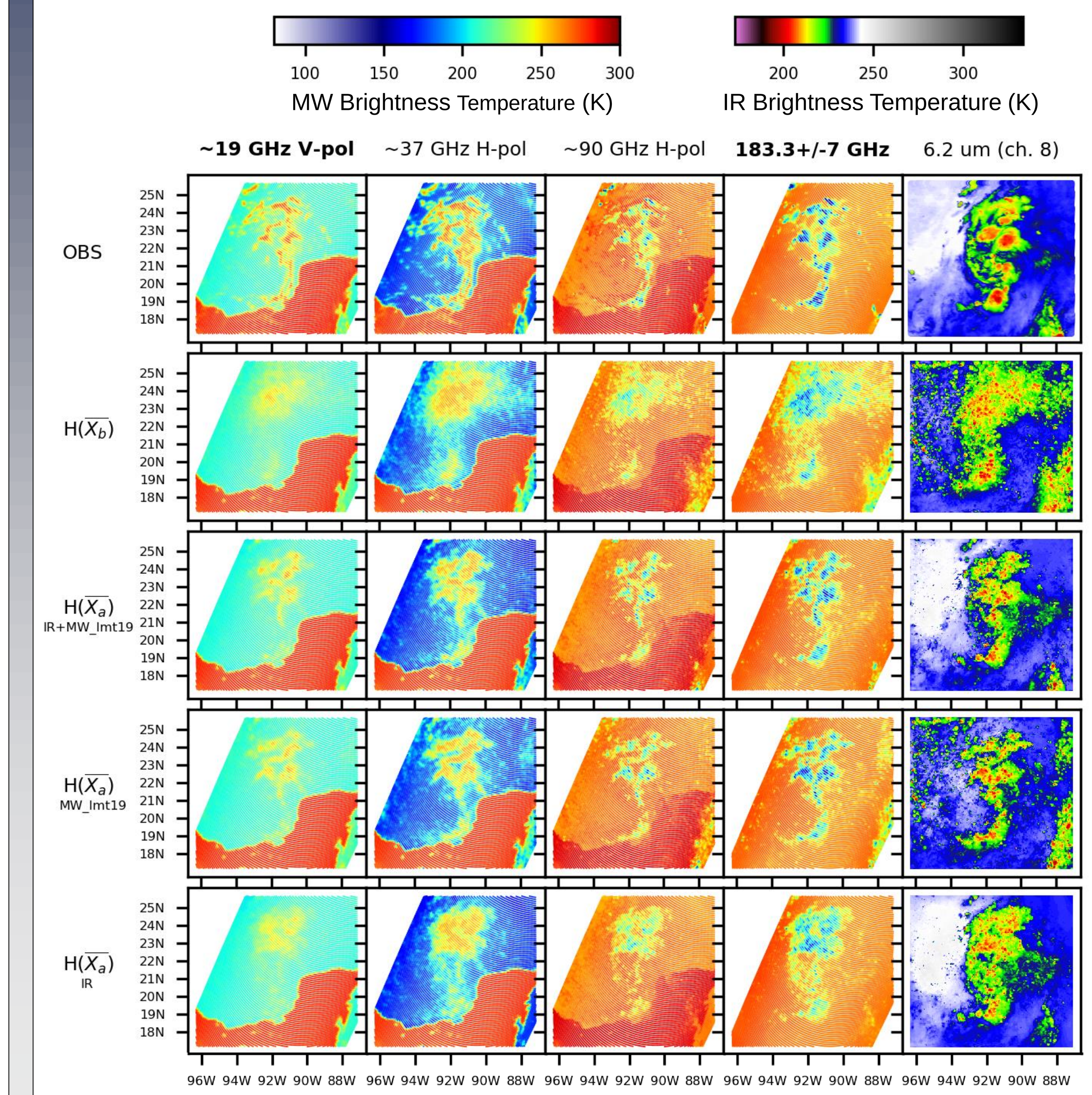

Figure 4 (top). Demonstration of various experiments of GMI microwave, IR and HPI assimilation for Harvey (2017) at 12 UTC 23 August. Observed BTs (top) are compared EnKF (2nd row) background and (remaining rows) analyses.

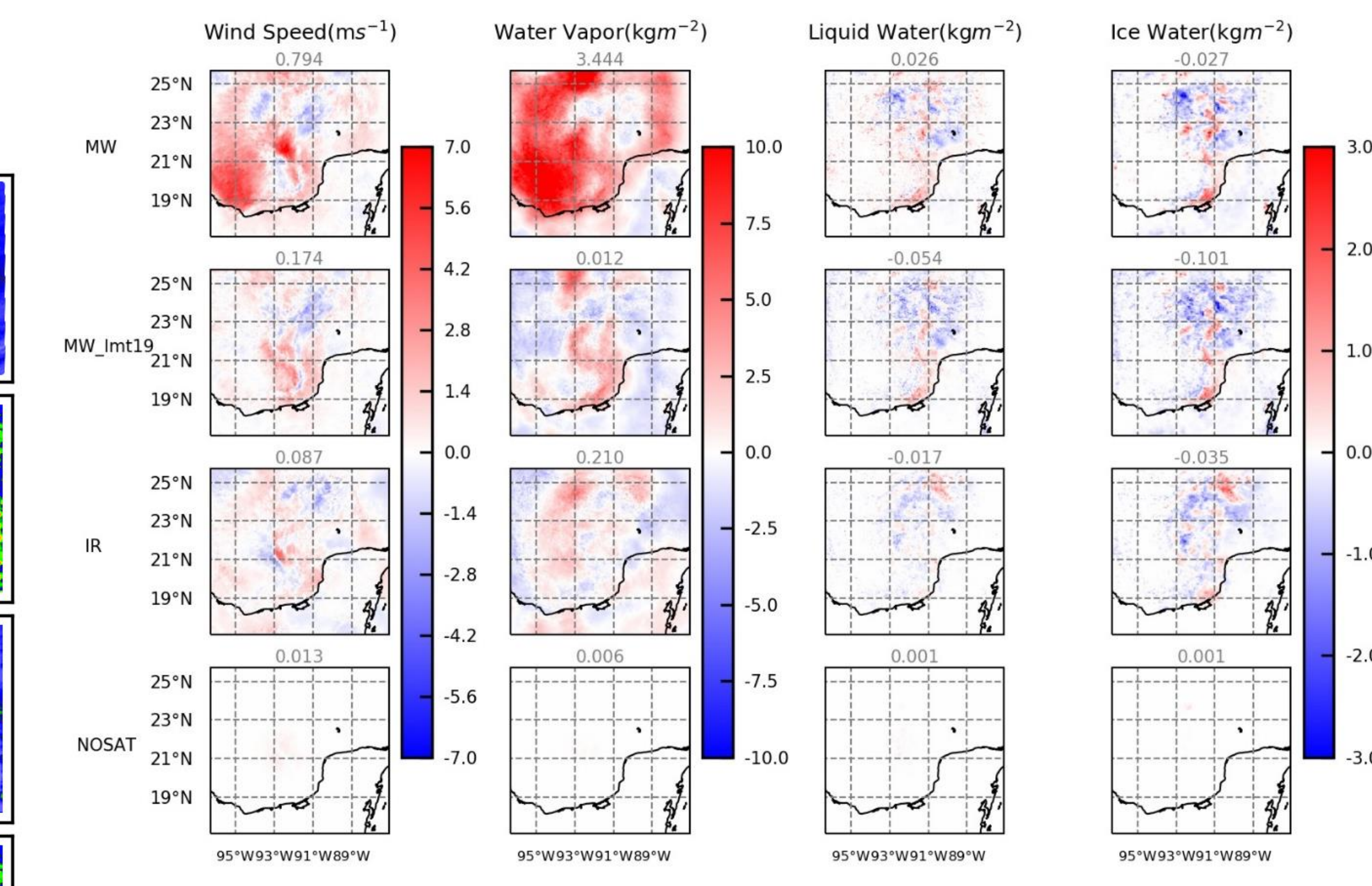

Figure 5 (top). Increments to a selection of variables from different observation selection experiments at 13 UTC 23 August.

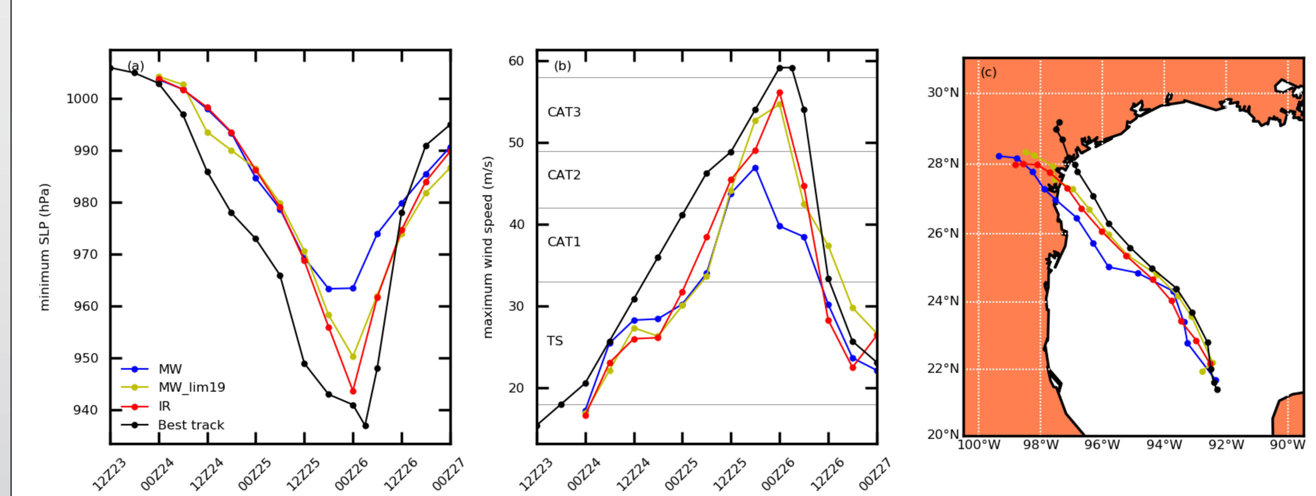

Figure 6 (top). Harvey (2017) central minimum sea-level pressure, maximum 10-m wind speed, and center of circulation track Best Track, compared with forecasts initialized from 24 Sept. 00 UTC EnKF analysis from a selection of experiments.

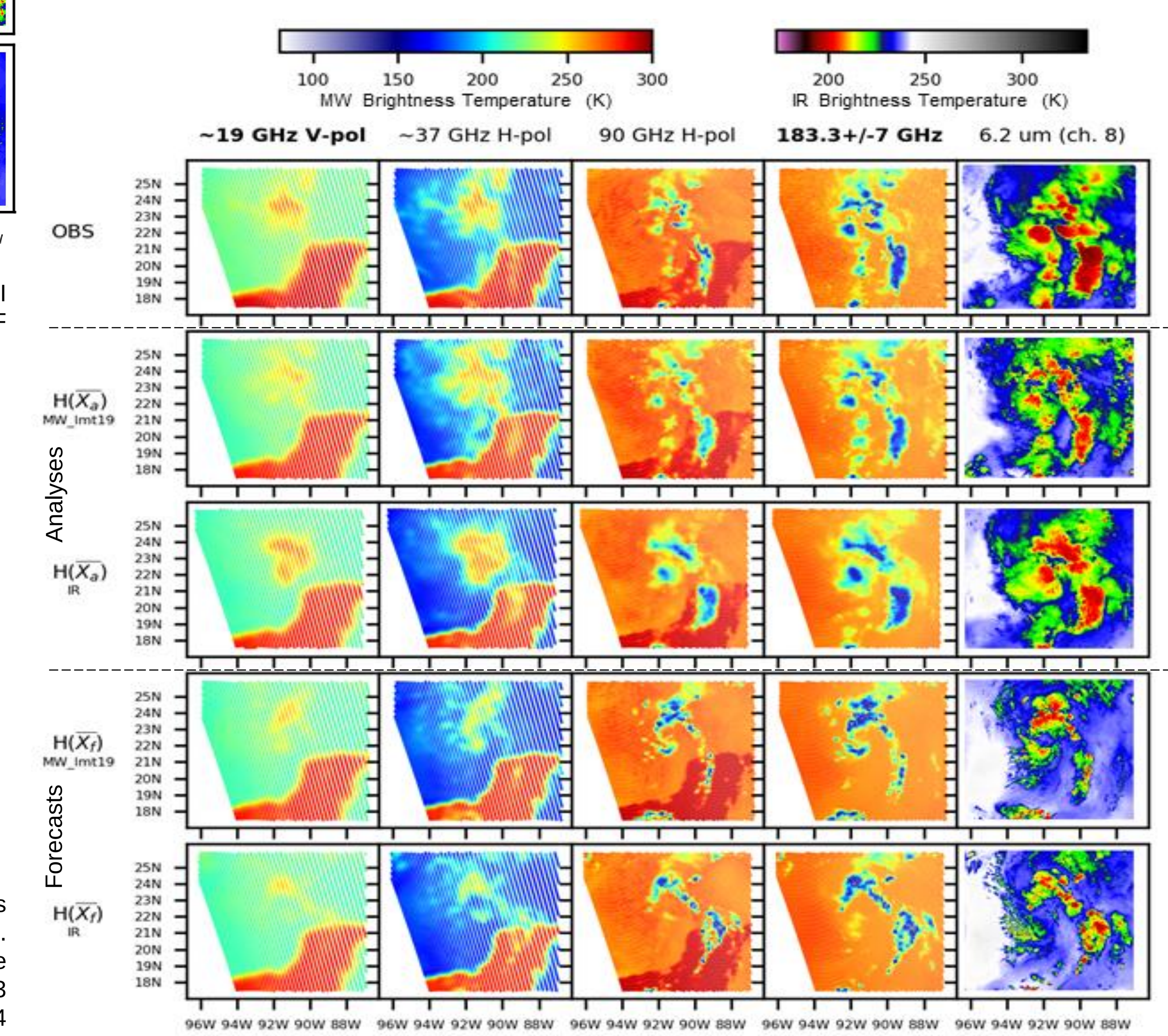

Figure 7 (right). (Row 1) Four observed (*OBS*) PMW BTs from the DMSP–F18 SSMIS overpass at 2356 UTC 23 Aug (Cols. 1-4) along with the ABI channel 8 BTs at 00 UTC 24 Aug (Col. 5). Simulated PMW (Cols. 1-4) and IR (Col. 5) BTs based on (Row 2) the EnKF analysis of the *MW_lmt19* experiment and (Row 3) the EnKF analysis of the IR experiment valid at 19 UTC 23 Aug. Row 4 is identical to Row 2 and Row 5 to Row 3 but for the 5-hour forecasts at 00 UTC 24 Aug initiated from the 1900 UTC 23 August analysis.

Points of Discussion

- Generally, assimilation of IR BTs leads to lower MW BTs in the analysis, while 19-GHz and 183-GHz assimilation raises MW BTs.
- Early EnKF cycle background MW brightness temperatures (BTs) correspond well with observations.

- Biases between modeled and observed 19 GHz clear-sky brightness temperatures
  - Assimilation produces strong increments in water vapor and surface wind speeds (assumed non-physical)
  - Water vapor analysis from *MW* experiment leads to bad forecast (not shown)
  - Bias is worse for some sensors than others (e.g., SSMIS on F18)
  - NASA PPS level 1c intercalibrated brightness temperatures seems to have less bias
- *IR+MW_lmt19* lead to worse forecast than *MW_lmt19* (not shown)
  - Should water vapor (and other variables?) increments from clear-sky observations be vertically localized according to their weighting function?
- Level 1c intercalibration produces a collection of similarly-formatted observation files (hdf5) that includes cross-track scanning sounders (MHS, ATMS). We will test including observations from these sensors.
- Early morning/afternoon (UTC) gaps between MW imaging overpasses are troublesome
  - Congress: more satellites, please! There is also unfortunate clustering of DMSP drifting orbits.

Conclusions and Future Work

- Preliminary experiments assimilating microwave (MW)+IR observations produce promising results, while helping to uncover new challenges and serving as a testbed
- Ongoing work:
  - Switching to NASA PPS level 1c intercalibrated MW brightness temperatures, revisit assimilating 19V clear-sky observations
  - Follow Minamide et al. (2019, JAS) to begin assimilation at 22 Sept. 12 UTC
- Future work:
  - Greater assessments of precipitation representation with assimilating MW once having created better analyses and forecasts (the 22 Sept. 12 UTC cycling)
  - Experiment with vertical localization in clear-sky
- Potential work:
  - Optimize AOEI and SOI parameters for microwave BT assimilation
  - Optimize IR assimilation frequency—give more influence to MW assimilation
  - Better CRTM MW cloud scattering, or different forward modeling techniques

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